



Early Prediction of Student Academic Performance Using Machine Learning

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Oluwaseun Bukonla Adedeji*, Akorede Ayoola Asanre, Ademola Abiodun Omilabu, Godwin Oluseyi Odulaja, Bolanle Lateefat Abimbola, Sulaimon Olawale Nosiru, Odunayo Damilola Osofuye

Abstract:

Background: As the database grows, predicting students' academic performance becomes more difficult. Traditional methods often overlook students with exceptional achievements and fail to fully track their progress. Although traditional assessments like exams and assignments provide valuable insights, they may not consider all factors affecting performance, such as socioeconomic status and engagement rates.

Aims: This study develops a predictive model aimed at classifying students' academic performance in higher education.

Methods: Using a combination of machine learning algorithms. Data collected from the Department of Computer Science and the Department of Mathematics at Tai Solarin University of Education was analyzed through the mutual information method to identify important factors. The model was created and tested using Google CoLaboratory, employing two algorithms: Support Vector Machines (SVM) and Decision Trees (DT). The accuracy of the models was measured using important indicators, including accuracy, precision, and the F-measure.

Results: This study shows that machine learning techniques can effectively identify student performance early, with SVM achieving 100% accuracy, enabling quicker involvements and better resource allocation.

Conclusion: Additionally, it supports evidence-based decision-making in educational institutions, which helps improve student encounter and enhances learners retention.

Keywords: Academic Performance, CoLaboratory, Machine Learning, Model, Performance Indicators,

1. INTRODUCTION

Predicting the success of students is essential for tailoring classroom instruction, enabling timely action and advancing learning (Deda et al., 2021; Alangari & Alturki, 2020). Educational instructors have traditionally depended on series of tools such as tests, presentation, and homeworks to assess learners success (Tsiakmaki et al., 2018; Rizwan et al., 2025; Karim-Abdallah et al., 2025; Ali et al., 2025; Stasolla et al., 2025). While these methods give us useful information about how well students understand, they often give just an overview of academic success, missing nuanced interactions between different performance-related factors (Salal & Kumar, 2019; Yağcı, 2022; Aydın, 2017; Baashar et al., 2022; Dabhade et al., 2021).

Machine learning (ML) and educational analytics are increasingly being used to analyze educational data (Tahiru et al., 2023; Albahli, 2025; Esmat & Pitts, 2020; Dewi & Widiastuti, 2020; Canagareddy et al., 2019). These algorithms can accurately profile students' learning behaviors (Falát & Piscová, 2022; Romero & Ventura, 2020), predict academic performance and customize learning experiences (Hassan et al., 2022; Ibarra-Vazquez et al., 2024). Techniques like deep learning and reinforcement learning enhance prediction accuracy by identifying complex patterns in large datasets (Khan et al., 2025).

Machine learning methods provide several benefits over single-algorithm prediction models (Karalar et al., 2021). By using more than one models, these methods can take advantage of their strengths of each while minimizing their, thus improving prediction accuracy and reliability (Hussain & Khan, 2023). Additionally, these approaches utilize a wide variety of data and modeling techniques, offering a more in-depth exploration of the factors influencing predictions (Angeioplastis et al., 2025; Ramaswami et al., 2019; Karalar et al., 2021). Ensemble modeling is commonly applied across various machine learning tasks, such as classification, regression, and clustering, and has been shown to boost predictive performance, reduce variation, and enhance model robustness compared to single-model methods. Achieving optimal outcomes with ensemble modeling requires careful tuning of hyperparameters, selection of different base models, and

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attention to processing resources (Tinajero et al., 2020; Shahid Wazir et al., 2025).

Higher education institutions face the ongoing challenge of attracting students who can meet diverse academic demands. Institutions must find ways to enhance students' learning experiences at all levels (Kordbagheri et al., 2025).

Setting of appropriate enrollment policies help in predicting academic success, while preventing poor performance. Traditional assessment methods like grades on standardized tests and in classes, have significant shortcomings (Stasolla et al., 2025; Kordbagheri et al., 2025).

Sometimes, these methods depend on the total evaluations that offer retrospective insights into learners' abilities but have little predictive power for aftermath performance. Also, traditional tests might not cover all of a student's skills, knowledge, and abilities, which could lead to assessments that are incomplete or unfair (Khan et al., 2025; Rizwan et al., 2025). They might also overlook non-academic factors influencing success, such as socioeconomic status, motivation, learning preferences, and mental health. Ignoring these variables can arrive at incorrect predictions and lost chances for intervention. Moreover, previous evaluations tend to be labor-intensive, time-taking, and subject to human biases, making them less scalable and cost-effective for large-scale predictive modeling efforts.

This study bridges this gap by developing a predictive model that employs an ensemble of machine learning algorithms to classify students' academic performance in

higher education based on factors influencing academic success. On-time recognition of academic issues can enable prompt support, personalized learning experiences, and better overall student results. Recognizing students who are struggling on time allows educators to offer tailored measures—such as teaching, counseling, or additional resources—to address academic challenges and help prevent students giving up.

2. MATERIAL AND METHOD

The departmental records provided relevant data related to the assessment of students' academic performance. Table 1 outlines the features considered while classifying academic achievement. The characteristics in the dataset were selected with the use of mutual information method. Based on the identified features, the ensemble model for classifying academic achievement was developed with different machine learning techniques.

Simulation of predictive models were done through the holdout method, using Google CoLaboratory, a Python Jupyter notebook for Gmail users. We ran five simulations for each algorithm. The training dataset was used to make the model. We then tested the models against a test dataset using a number of performance metrics, such as accuracy, true positive rate, false positive rate, precision, and f-measure.

2.1 Figures and Tables

Table 1. Identifying characteristics linked to creditworthiness

Class of Variable	Name	Label values
Socio-Demographic Information	Gender	Categorical (Male, Female)
	Age at Admission	Number – Int type
	State of Origin	Categorical
UTME Results	English	Number – Int Type
	Mathematics	Number – Int Type
	Chemistry	Number – Int Type
	Physics	Number – Int Type
	English	Number – Int type
	Mathematics	Number – Int type
	Chemistry	Number – Int type
O'Level Results (SSCE)	Physics	Number – Int type
	Agricultural Science	Number – Int type

	Biology	Number– Int type
	Economics	Number– Int type
	Geography	Number – Int type
	Technical Drawing	Number – Int type
	Further Mathematics	Number – Int type
First year Results	1 st Semester CGPA	Number – Float type
	2 nd Semester CGPA	Number – Float type
Target Class	Graduating Class of Degree	Categorical (1st Class, 2.1 , 2.2, 3 rd Class)

3. RESULTS DISCUSSION

3.1 Result

The transformation of categorical string-valued features into number types were displayed in the result, along

with an evaluation of the significance of these attributes. Next, the simulation outcome and the evaluation of the comparative analysis of both machine learning models were examined using various performance criteria

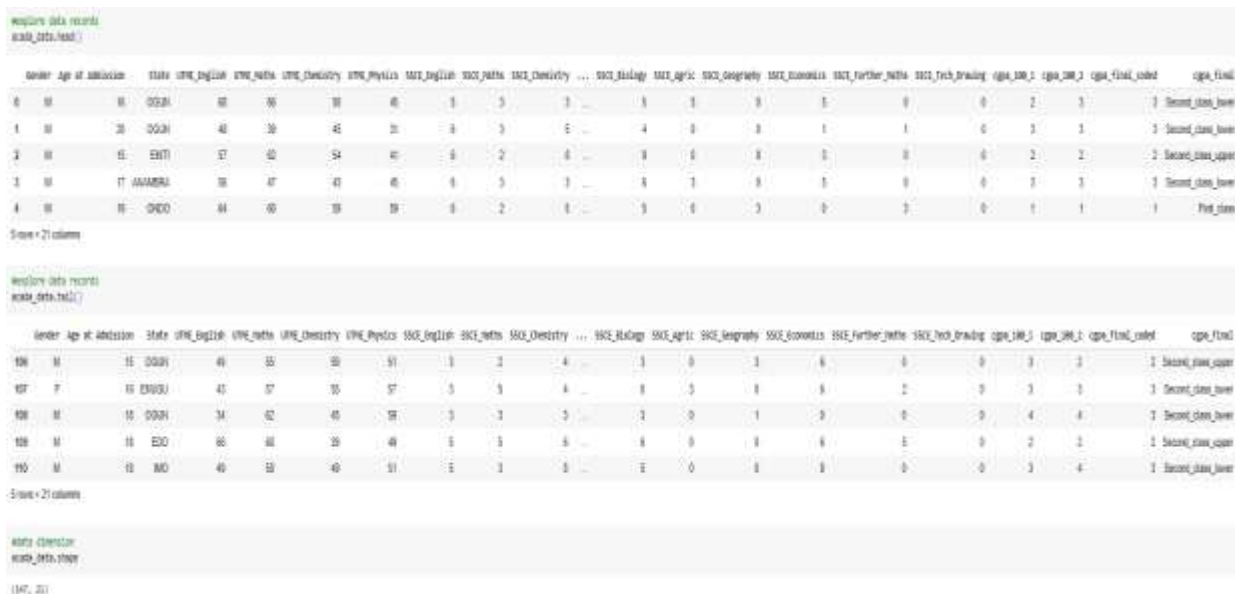


Figure 1. A screenshot of the visualization of the dataset's contents

This diagram reveals a screenshot of the dataset descriptions, which show the values of the features that were found in the dataset that was collected for this study.

The figure shows that most of the features were saved as numbers, but gender and state were saved as strings with categories.

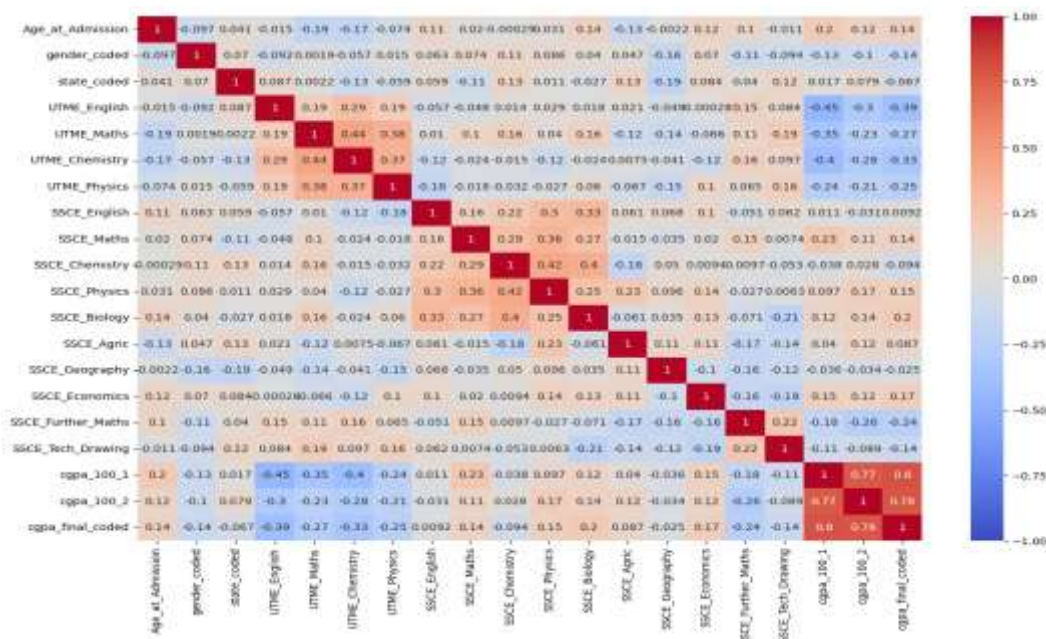


Figure 2. shows a heatmap of how features are related to each other

Figure 2 shows how strongly the attributes are related to each other. Darker colors mean stronger correlations, while lighter colors mean weaker correlations.

Additionally, blue hues denoted a positive association while red hues indicated a negative correlation. However, the values shown in the final row, referred to as cpga final, were analyzed because the study's focus is on the relationship between the features and the classification of students' academic achievement.

The correlation between the attributes and the classification of students' academic achievement is shown by the values in the cell of the last row. The mutual information measure is used to graphically represent feature importance in decreasing order in Figure 2.

Figure 2 illustrates how much information about the categorization of students' academic success can be described by each feature found in the dataset based on the data gathered about them in the dataset.

3.2 Discussion

Table 3. Explain how many records were used in total over the course of five simulations to train and test prediction mode

Simulation#	Train Data					Test Data					
	2.1	2.2	First	Third	Total	2.1	2.2	First	Third	Total	
Simulation (50/50)	1	29	18	4	10	61	17	10	8	15	50
Simulation (60/40)	2	33	20	5	13	71	10	8	10	12	40
Simulation (70/30)	3	37	26	4	16	81	7	7	10	6	30

The assessment of the predictive models developed during five simulations using the machine learning and ensemble modeling methods employed in this research is presented in this section. Each simulation's outcomes are displayed first, then the algorithms' performance outcomes.

Simulation Results for Predictive Models

The results of using a machine learning algorithm—specifically, the support vector machines (SVM) classifier—are covered in this section. In order to simulate the model, the dataset was split into train and test datasets. Five simulations were used, with 50/50, 60/40, 70/30, 80/20, and 90/10 percent of the dataset being used to train and test the prediction model.

Table 3 shows how many records were used for each of the simulations examined in this study. As mentioned before, test data were utilized to evaluate the predictive models' performance using a range of performance metrics, whereas the train datasets were utilized to create the predictive mode.

Simulation (80/20)	4	43	30	2	16	91	4	7	5	4	20
Simulation (90/10)	5	48	39	5	19	101	2	3	3	2	10

Figure 3 displays the confusion matrices that are needed to arrive at the outcome of the evaluation of the machine learning model used in simulation 1 on the test dataset. The Support Vector Machine classifier found that all 17 real 2nd-class upper records, all 10 real 2nd-class lower

records, all 8 real 1st-class records, and all 15 real 3rd-class records were classified correctly, giving an accuracy of 100%.

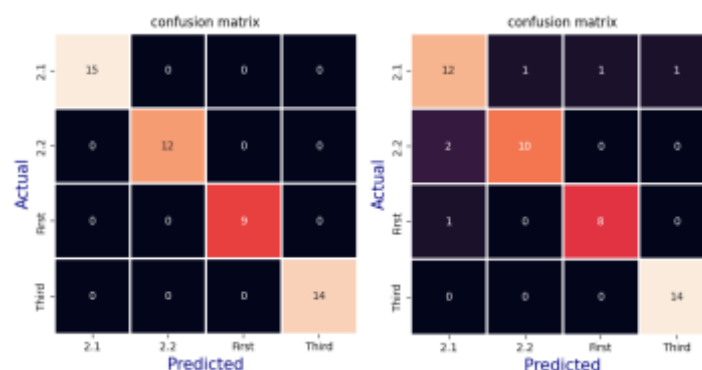


Figure 3. Confusion matrices used in simulation 1 to assess Decision Trees (right) and Support Vector Machines (left)

Figure 4 shows how the results of the evaluation of the machine learning model in simulation 2 using the test dataset were explained by the confusion matrices. A 100% accuracy rate was achieved by correctly

classifying all 10 actual 2nd-class upper records, all 8 actual 2nd-class lower records, all 10 actual 1st-class records, and all 12 actual 3rd-class records using the Support Vector Machine classifier.

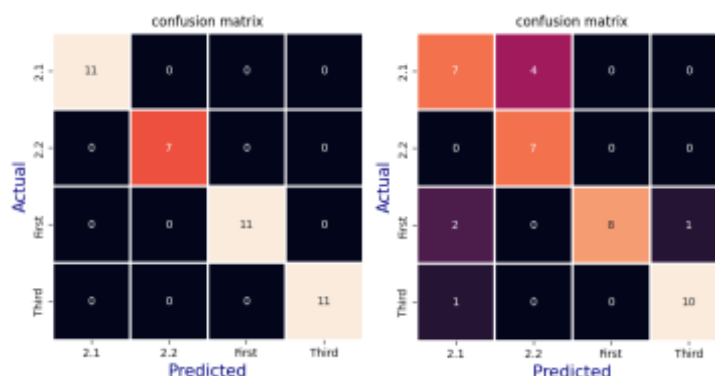


Figure 4. Confusion matrices used in simulation 2 to assess Decision Trees (right) and Support Vector Machines (left)

Figure 5 reveals the confusion matrices needed to assess test dataset-based evaluation results of both machine learning models utilized in simulation 3. A 100% accuracy rate was achieved by correctly classifying all

seven confirmed 2nd-class upper records, all seven confirmed 2nd-class lower records, all ten confirmed 1st-class records, and all six confirmed 3rd-class records using the Support Vector Machine classifier.

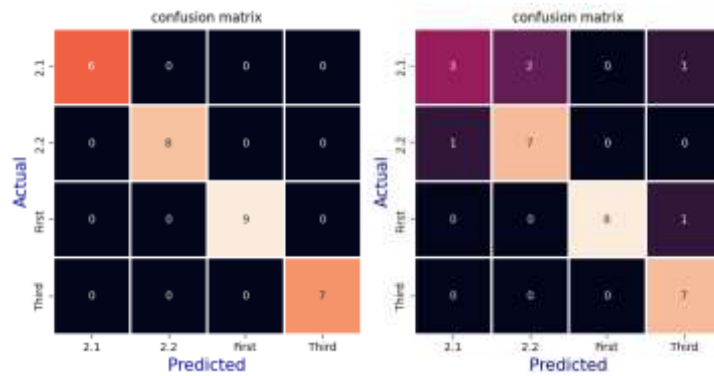


Figure 6. Confusion matrices used in simulation 4 to assess Decision Trees (right) and Support Vector Machines (left)

Figure 7 reveals the confusion matrices needed to assess the evaluation outcome of the two machine learning models applied to the test dataset in simulation 5. A 100.0% accuracy rate was achieved by correctly classifying all two actual second-class upper records, all

three confirmed 2nd-class lower records, all three confirmed 1st-class records, and all two confirmed 3rd-class records using the Support Vector Machine classifier.

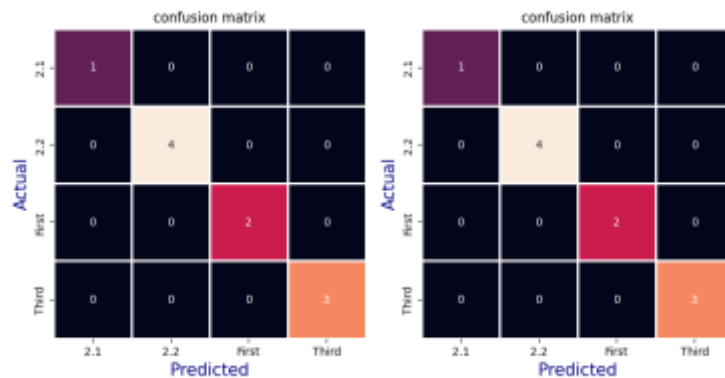


Figure 7. Confusion matrices used in simulation 5 to assess Decision Trees (right) and Support Vector Machines (left)

Table 4. Results of the assessment of predictive models across five simulations utilizing performance metrics

Simul	Algorit	Corr	Accur	Precision				Recall				F1-Score			
ation#	hm	ect	acy	2.1	2.2	Fir	Thi	2.1	2.2	Fir	Thi	2.1	2.2	Fir	Thi
		Reco	(%)			st	rd			st	rd			st	rd
		rds													
Simulat															
ion 1	SVC	50	97.0	0.9	0.9	0.9	0.98	0.9	0.9	0.9	0.98	0.9	0.9	0.9	0.97
				9	8	8		8	7	7		7	8	7	
	DT	44	88.0	0.8	0.9	0.8	0.93	0.8	0.8	0.8	1.00	0.8	0.8	0.8	0.97
				0	1	9		0	3	9		0	7	9	

Simulat

ion 2	SVC	40	96..0	0.9	0.9	0.97	0.9	0.9	0.9	0.97	0.9	0.9	0.9	0.98	
				8	8		8	8	7		8	7	8		
	DT	32	80.0	0.7	0.6	1.0	0.91	0.6	1.0	0.7	0.91	0.6	0.7	0.8	0.91
				0	4	0		4	0	3		7	8	4	

Simulat

ion 3	SVC	30	97.0	0.9	0.9	0.9	0.97	0.9	0.9	0.9	0.97	0.9	0.9	0.9	0.98
				8	7	8		7	7	8		7	7	7	
	DT	25	80.0	0.7	0.7	1.0	0.78	0.5	0.8	0.8	1.00	0.6	0.8	0.9	0.88
				5	8	0		0	8	9		0	2	4	

Simulat

ion 4	SVC	20	96.0	0.9	0.9	0.9	0.97	0.9	0.9	0.9	0.98	0.9	0.9	0.9	0.98
				7	7	7		8	8	8		7	7	7	
	DT	18	90.0	0.8	0.8	1.0	1.00	0.8	0.8	1.0	1.00	0.8	0.8	1.0	1.00
				0	3	0		0	3	0		0	3	0	

Simulat

ion 5	SVC	10	99.0	1.0	1.0	1.0	1.00	1.0	1.0	1.0	1.00	1.0	1.0	1.0	1.00
				0	0	0		0	0	0		0	0	0	
	DT	9	90.0	0.5	1.0	1.0	1.00	1.0	0.7	1.0	1.00	0.6	0.8	1.0	1.00
				0	0	0		0	5	0		7	6	0	

3.2.1 Implications

This study implies that machine learning models can detect patterns that contribute to the poor performance of students such as low attendance, poor engagement, low CGPA thereby enabling early intervention such as mentoring, counseling

and tutoring which will definitely helps to reduce dropout rates.

3.2.2 Research Contribution

It supports evidence-based decision making in educational institutions, which help improves student encounter and enhances learners retention.

3.2.3 Limitations

In complete, noisy or inaccurate student records reduce model reliability, meanwhile, some important factors are hard to measure such as motivation, emotional state and mental health. A model trained in one university may not work well in another due to different curricula, cultural differences and teaching styles.

3.2.4 Suggestions

Focus should be on early intervention and not labeling or tagging students as 'failure'. Continuous updating and validating of models should be encouraged also retraining models with new data regularly.

4. CONCLUSION

The study looked into how well Support Vector Machine, a machine learning technique, classified and predicted student performance. The Tai Solarin University of Education's Department of Computer Science provided the datasets. In order to simulate the model, the dataset was split into train and test datasets. Five simulations were used, with 50/50, 60/40, 70/30, 80/20, and 90/10 percent of the dataset being used to train and test the prediction model. According to the study's findings, machine learning models especially Support Vector classifiers, which achieve 100% accuracy are excellent at categorizing students' academic achievement.

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6. AUTHOR CONTRIBUTION STATEMENT

Conceptualization: the study idea research objectives and overall design The were developed by O.B, and O.D.

Methodology: The research methodology, including the machine learning framework and experimental design, was designed by O.B.

Data Collection: Data acquisition, survey design and dataset preparation were carried out by O.B and AAA.

Data Analysis and Validation: Data cleaning, preprocessing, implementation, model testing, evaluation and validation. By O.B and O.D

Review and Editing: Critical review and editing of the manuscript were done by A.A.O, G.O, B.L and N.S

AUTHOR INFORMATION

Corresponding Authors

Oluwaseun Bukonla Adedeji, Tai Solarin Federal University of Education, Nigeria.

 <https://orcid.org/0000-0002-6721-5028>

Email: oluwaseunfunmi4god@yahoo.com

Author

Akorede Ayoola Asanre, Tai Solarin Federal University of Education, Nigeria.

 <https://orcid.org/0000-0003-2787-2346>

Email: Asanreaa@tasued.edu.ng

Ademola Abiodun Omilabu, Tai Solarin Federal University of Education, Nigeria.

 <https://orcid.org/0000-0002-5383-5074>

Email: omilabuaa@tasued.edu.ng

Godwin Oluseyi Odulaja, Tai Solarin Federal University of Education, Nigeria.

 <https://orcid.org/0000-0002-9825-2884>

Email: odulajago@tasued.edu.ng

Bolanle Lateefat Abimbola, Tai Solarin Federal University of Education, Nigeria.

 <https://orcid.org/0009-0002-1475-2222>

Email: abimbolabl@tasued.edu.ng

Sulaimon Olawale Nosiru, National Open University of Nigeria, Nigeria.

 <https://orcid.org/0000-0002-0993-3822>

Email: snosiru@noun.edu.ng

Odunayo Damilola Osofuye, Covenant University Canaanland Ota, Nigeria.

 <https://orcid.org/0009-0003-9093-4906>

Email: Odunayo.osofuye@covenantuniversity.edu.ng

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